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Day-ahead tariffs for the alleviation of distribution grid congestion from electric vehicles

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ABSTRACT

An economically efficient day-ahead tariff (DT) is proposed with the purpose of preventing the distribution grid congestion resulting from electric vehicle (EV) charging scheduled on a day-ahead basis. The DT concept developed herein is derived from the locational marginal price (LMP), in particular the congestion cost component of the LMP. A step-wise congestion management structure has been developed whereby the distribution system operator (DSO) predicts congestion for the coming day and publishes DTs prior to the clearing of the day-ahead market. EV fleet operators (FOs) optimize their EV charging schedules with respect to the predicted day-ahead prices and the published DTs, thereby avoiding congestion while still minimizing the charging cost. A Danish 400V distribution network is used to carry out case studies to illustrate the effectiveness of the developed concept for the prevention of distribution grid congestion from EV charging. The case study results show that the concept is successful in a number of situations, most notably a system over-load of 155% can be successfully alleviated on the test distribution network.

Keywords: Day-ahead tariff, Congestion alleviation, Distribution grid, Locational marginal price, Electric vehicle charging management

1 Introduction

With increasing levels of intermittent renewable generation penetration in the power system, in a future when electric vehicles (EVs) assumed a significant role, their use to balance the

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power fluctuations introduced by intermittent generation would become an attractive option. Incorporating the transport sector into the electricity sector by replacing conventional internal combustion engine (ICE) vehicles with EVs can help reduce green house gas (GHG) emissions from the transport sector.

Denmark presents a unique opportunity for renewable energy utilization and EV deployment. The current wind power penetration level in Denmark is approximately 20%. The Danish government has set a target of 50% penetration of wind power by 2025 [1]. The average driving distance in Denmark is approximately 40 km per day [2]. A fully charged 25 kWh battery can provide sufficient energy to meet daily driving energy requirements in most cases. If additional energy is required, EV batteries can be recharged during the day, where the appropriate charging infrastructure is in place. Therefore, from both the system balancing and end-user driving perspectives, it is an interesting option to implement the integration EVs into the power system.

Nonetheless, the electrification of transportation will lead to significant challenges for the power system. These challenges are expected to manifest at several levels of the power system, from increased generation capacity requirements to congestion on distribution networks. Each will present unique conditions and solutions, and will require substantial efforts on the part of power system engineers and other system participants in the coming years to ensure continued system reliability.

Grid congestion results from excessive demand beyond the design limitations of the system. Congestion from EVs can be observed at the medium voltage (MV) level, as a number of studies demonstrate [3]-[4]. Many studies have been conducted analyzing congestion issues on the MV network, however they also note that the problems likely originate on the distribution network, and as such, analysis of this network should be conducted as the primary stage of congestion studies [3], [5], [6].

The degree of grid congestion, i.e. the percentage of overloading, is dependent on a number of factors including local grid rating and topology, penetration and distribution of EVs, and charging management procedures. Coordinated charging appears to be an effective means of allowing increased penetration of EVs without violating grid constraints. There is some

incongruity on the optimal manner in which to coordinate charging, with a number of different objectives proposed, including maximization of EV penetration [3], minimization of losses [4], and minimization of customer charging costs [7]-[8]. The study conducted in [7] shows that the computational power required to handle grid constraints at the distribution level in the linear programming optimization of EV charging management is quite significant.

An alternative method to prevent grid congestion is the inclusion of devices in chargers to detect voltage and halt charging when the voltage at the point of connection drops below a set threshold. Alternatively, the power factor could be adjusted to rectify the voltage drop. These methods are mentioned in a number of papers [9]-[11], however, it is unclear how effective these measures will be at high levels of EV penetration.

There are many approaches to congestion management in transmission systems, depending on the electricity market structure. The congestion management methods can be categorized into three groups: the Optimal Power Flow (OPF) based method, the price area congestion control method and the transaction-based method [12]. The OPF based congestion management method is based on a centralized optimization and is considered to be the most accurate and effective congestion management method. A price-signal based congestion management scheme has been proposed to eliminate congestion by generation rescheduling determined by congestion prices within an OPF framework [13]. A one-step congestion management method was proposed in [14] to manage congestion in hybrid markets. The proposed congestion management method incorporates the support from reactive power manipulation and the embedded cost of reactive power, and OPF is used to determine the congestion management scenario. A new transmission pricing scheme based on point-to-point tariffs for pool markets has been proposed based on pay as bid (PAB) to provide price signals to promote the maximum use of the existing transmission network, encourage appropriate bidding behaviors, and reduce market power and price spikes [15].

A common theme in the literature in the area of optimal EV charging management is that of a commercial entity that oversees the charging of EVs on behalf of the end-use private consumer; the terminology for such an entity varies, but it is henceforth referred to as a fleet operator (FO) in this paper. FOs have been found to be particularly useful for the alleviation of grid congestion,

as the geographical and temporal diversity of their portfolios can be exploited to reallocate charging to locations and times of low demands, while still respecting the energy requirements of each EV. In addition, as a commercial entity, their incentive for profit maximizing behavior is larger than that for individual consumers, resulting in a higher elasticity of demand and effective response to price signals.

In this paper, a day-ahead grid tariff has been developed to prevent distribution grid congestion from electric vehicle (EV) charging from a day-ahead planning perspective. The DT concept developed herein is derived from the locational marginal price (LMP), in particular the congestion cost component of the LMP. A step-wise congestion management scheme has been developed whereby the distribution system operator (DSO) predicts congestion for the coming day and publishes DTs prior to the clearing of the day-ahead market. EV fleet operators (FOs) optimize their EV charging schedules with respect to the predicted day-ahead prices and the published DTs, thereby avoiding congestion while still minimizing the charging cost.

The concept of distribution grid congestion alleviation using day-ahead tariffs (DTs) is explained in detail in Section 2. The determination of DTs is presented in Section 3. The optimal EV charging algorithm with respect to both day-ahead prices and DTs is described in Section 4. Case studies have been implemented using a Danish 0.4kV grid and are presented in Section 5 to illustrate the effectiveness of the proposed DT concept. Finally, conclusions are drawn based on the case study results.

2 Distribution grid congestion alleviation using DTs

The central requirement of an optimal day-ahead dynamic tariff concept is essentially to effectively alleviate congestion, while ensuring economic efficiency.

The tariff concepts are roughly divided into two categories – integrated and stepwise. An integrated model involves the implementation of a fully nodal pricing system where both system balance and grid congestion are settled in a single step, e.g. FOs submit demand bids to the day-ahead market and are then subject to locational prices. This is considered to be the most socio-economically optimal solution as the electricity price reflects its true cost. Implementing this on the distribution network however would require a complete overhaul of the current Nordic

day-ahead market (DAM) and would be difficult to introduce, particularly from the perspective of complexity and market participant acceptance.

In a step-wise tariff scheme, the system balance and grid congestion are handled separately. Generally, this requires prediction from one or more market participants. DSOs can predict demand and determine tariffs based on their predictions, or FOs can predict tariffs and optimize their demand so as to avoid the additional tariffs, thereby also avoiding congested periods and locations. It is considered difficult to achieve socio-economic optimality in a step-wise tariff concept, however it is very simple to introduce into the Nordic DAM, as it currently exists.

The DT scheme developed here is based on the concept of a step-wise process where grid congestion is managed prior to the determination of system balance on the day-ahead market. The proposed scheme is intended to fit directly into the Nordic electricity market as it currently stands. This will ensure ease of acceptance from all market participants.

A key concern with a step-wise process is the difficulty in attaining a socio-economically optimal solution. In this scheme, it is proposed that the tariffs will be based on the locational marginal price of electricity, thus they will reflect the true cost of generation, transmission and distribution of electricity. For this purpose, a nodal pricing market is simulated by the DSO, however the price is implemented in the format of tariffs for flexible demand (in this case EVs) thus avoiding alterations in the structure of the current DAM and unfair penalties for non-flexible demand.

The flowchart in Figure 1 explains the proposed step-wise distribution grid EV congestion alleviation scheme using DTs. The steps of implementing the proposed method are listed below.

- A. DSO predicts day-ahead prices of electricity for the coming day and EV driving patterns – the day-ahead price prediction will be influenced by the wind forecast, particularly as the penetration of low marginal cost generators such as wind increases. The driving pattern prediction will be based on historical driving data; the historical driving data could be from the transport authority or FOs.
- B. Based on the predicted day-ahead prices and EV driving pattern, the DSO forecasts the EV charging schedules of all EVs on the distribution grid with the most cost efficient EV charging scenario.
- C. The DSO runs an optimal load flow calculation based on predicted conventional and EV charging demand and determines locational marginal prices (LMPs) for each node in the distribution grid.

- D. DTs are determined based on the congestion cost component of the LMP and these will then be made available to the FOs prior to the market clearing of the day-ahead market.
- E. FOs bid into the day-ahead market based on the published tariffs and predicted day-ahead prices.

The concept of the proposed step-wise distribution grid congestion alleviation from EVs using DTs is shown in Figure 2.

In the proposed concept, there is an assumption that all FOs are sensitive to the price signals and will try to come out the most economically efficient EV charging schedules based on both spot prices and varying grid tariffs. The diversity of FOs has not be considered in the current work and it will be investigated in the future work.

The proposed concept is quite dependent on the fact that the EV demands with DTs can adjust the EV demands in such a way that the predicted congestions in electric distribution networks can be alleviated. In reality, there could be mismatch between the predicted EV demands without DTs and the real EV demands. This mismatch could have a distortive effect on the efficiency of the proposed DT concept. This kind of mismatch could be handled by more real time market mechanism or direct control methods.

3 Determination of DTs

Locational marginal pricing is a pricing structure that reflects the marginal cost of electricity supply at each individual bus. The price reflects the marginal cost of generation as well as the costs associated with the physical constraints of the system. The LMP exposes producers and consumers to the true cost of energy delivery throughout the system. It can be decomposed into three constituent components; the marginal cost of generation, marginal cost of losses and the marginal cost of congestion [16].

AC optimal power flow (ACOPF) is typically used for LMP calculation. However, DC optimal power flow (DCOPF) is also widely used for LMP calculation due to its efficiency and acceptable accuracy. The DCOPF is considered to be sufficient in many cases [17]. In this case, for the calculation of LMPs, the DCOPF is a suitable option, particularly considering the marginal congestion cost used for determining DTs and the large number of nodes on the distribution system. In industry, DCOPF has been employed by several software tools for chronological

LMP simulation and forecasting, such as ABB GridViewTM, Siemens Promod, GE MAPSTM and PowerWorld [18].

In the proposed DT scheme, the tariffs are determined by the marginal cost of congestion; the marginal cost of losses is not a core element for the determination of the DTs. Therefore, the lossless DCOPF is used to calculate the LMPs.

The DCOPF without losses can be represented by the following optimization formulation.

Objective function

$$\text{Min} \sum_{i=1}^N c_i \times G_i \quad (1)$$

subject to the following equality and inequality constraints:

$$\sum_{i=1}^N G_i = \sum_{i=1}^N D_i \quad (2)$$

$$\sum_{i=1}^N PTDF_{k-i} \times (G_i - D_i) \leq \text{Limit}_k \quad k = 1, 2, \dots, M \quad (3)$$

$$G_i^{\min} \leq G_i \leq G_i^{\max}, \quad i = 1, 2, \dots, N \quad (4)$$

where N is the bus number, M is the line number, c_i is the generation cost at bus i (DKK/MWh), G_i is the generation dispatch at bus i (MWh/h), G_i^{\max} and G_i^{\min} are maximum and minimum generation output at bus i , D_i is the demand at bus i , $PTDF_{k-i}$ is the generation shift factor to line k from bus i , Limit_k is the transmission limit of line k (MW).

In the above DCOPF formulation, the power transfer distribution factors (PTDFs) are the sensitivities of branch flows to changes in nodal real power injections [19]. In general, the PTDFs depend on the operating point and topology of an electric power system. However, it has been demonstrated in [20] that the PTDFs are relatively insensitive to the operating point of an electric power system if the topology is fixed and there is

sufficient reactive power compensation to have voltages constant at all buses. Therefore, it is feasible to keep the PTDF matrix constant for the DCOPF calculation.

The Lagrangian function of the DCOPF is described by Eq. (5).

$$L = \left(\sum_{i=1}^N c_i \times G_i \right) - \lambda \times \left(\sum_{i=1}^N G_i - \sum_{i=1}^N D_i \right) - \sum_{k=1}^M u_k \left(\sum_{i=1}^N PTDF_{k-i} \times (G_i - D_i) - Limit_k \right) \quad (5)$$

where λ is the Lagrangian multiplier of the equality constraint of Eq. (2), μ_k is the Lagrangian multiplier of inequality constraint of Eq. (3).

The LMP at bus i can be calculated using Eq. (6).

$$LMP_i = \frac{\partial L}{\partial D_i} = \lambda + \sum_{k=1}^M u_k \times PTDF_{k-i} \quad (6)$$

where LMP_i is the LMP at bus i , λ is the locational marginal energy price and

$\sum_{k=1}^M \mu_k \times PTDF_{k-i}$ is the locational marginal congestion price.

The locational marginal congestion price reflects the real congestion cost and is used to determine the DTs. The DTs can be calculated by Eq. (7).

$$DT_i^t = \sum_{k=1}^M \mu_k^t \times PTDF_{k-i}^t \quad (7)$$

where DT_i^t is the DT at bus i of time step t , $\sum_{k=1}^M \mu_k^t \times PTDF_{k-i}^t$ is the marginal congestion price

at bus i for time step t . As μ_k^t is the Lagrangian multiplier for Eq. 3, it is only non-zero when the constraint is binding, thus during uncongested periods (when the component loading is below the defined limit) the LMP reverts to the marginal cost of generation and no tariff is applied.

A number of power systems across the world operate on a LMP based market. The remarkable example is the PJM in the east of USA. A few other examples are the New England system, the New York System, the Electric Reliability Council of Texas (ERCOT) system in the USA, the New Zealand system and the Alberta system in Canada [21]. The LMP reflects the marginal cost of electricity supply at each system bus. In order to determine the appropriate tariff

magnitude over a sufficient period, the LMP calculation has been altered whereby the electric distribution system is considered to contain only two generators, whose relative price difference corresponds to the maximum price difference during the optimisation period. Under this framework, during uncongested periods only one generator supplies power, and the system price corresponds to the predicted day-ahead price. During congested periods, where system loading exceeds a given threshold, the second generator supplies power in order to redirect power flow according to the congestion experienced. In this case the DT, or congestion component of the LMP, is non-zero and its magnitude is related to the system price profile; the appropriate DT magnitude is therefore determined.

4 Optimal EV charging management

The DT concept for the alleviation of distribution grid congestion is dependent on the assumption that FOs will optimize their fleet charging behavior in response to price signals from both predicted day-ahead prices and published dynamic tariffs. The tariffs are calculated based on the congestion cost component of the LMP, thus they are only active during periods of congestions. This has the effect of shifting charging demands from congested locations and times.

The objective function shown below is a linear expression, which inherently assumes that the FO is a price taker and cannot exert any market power [22]. For this study it is assumed that there are sufficient distinct FOs to ensure a competitive market where market power cannot be exercised. This will require a degree of market regulation to ensure, however this will likely only become an issue once high EV penetration levels are realized, at which point the market volume will ensure the economic viability of multiple FOs. If the FOs are allowed to exert market power, an alternative objective function is required. A quadratic programming optimization can account for alterations in the predicted day-ahead price due to gaming behavior from FOs [22].

The mathematical formulation of the optimization for FOs is shown below.

Objective Function

$$\min \sum_{t=1}^T \sum_{i=1}^I \sum_{n \in i} \left[E_{n,t} (C_t + DT_i^t) \right] \quad (8)$$

subject to the following EV charging constraints

$$0 \leq E_{n,t} w_{n,t} \leq E_{\max} \quad \forall t, n \quad (9)$$

$$SOC_{\min} \leq SOC_{init} + \sum_{t=1}^{\tau_n} E_{n,t} w_{n,t} - \sum_{t=1}^{\tau_n + \tau_{n,d}} E_{d,n,t} v_{n,t} \leq SOC_{\max} \quad \forall t, n \quad (10)$$

$$w_{n,t} + v_{n,t} \leq 1 \quad \forall t, n \quad (11)$$

$$w_{n,t}, v_{n,t} \in \{0,1\} \quad \forall t, n \quad (12)$$

where C_t is the predicted electricity day-ahead price at time t [DKK/kWh], DT_i^t is the DT at bus i for time t [DKK/kWh], $E_{d,n,t}$ is the driving Energy requirement for EV n during period t [kWh], E_{\max} is the maximum charging energy during period t [kWh], SOC_{\min} is the minimum battery state of charge (SOC), SOC_{\max} is the maximum battery SOC, SOC_{init} is the initial battery SOC, τ_n is the set of time at which vehicle becomes unavailable for charging, $\tau_{n,d}$ is the set of durations for which vehicle is unavailable for charging, $v_{n,t}$ is the binary parameter signifying EVs driving status - 1=driving and 0=available to charge, i is the bus index, n is the EV index, $E_{n,t}$ is the charging energy for EV n during period t [kWh], $w_{n,t}$ is the binary control variable signifying EVs charging status - 1=charging and 0=not charging.

The objective function ensures the total cost of charging is minimized considering both predicted day-ahead prices and published DTs.

The constraints guarantee that the battery SOC is at least sufficient to facilitate the driving energy requirement during the next driving period, while also allowing additional charging to satisfy future driving requirements, for example to take advantage of low cost periods. In addition to these driving constraints, the battery SOC is restricted to between SOC_{\min} and SOC_{\max} so as not to reduce the battery lifetime. E_{\max} determines the maximum charging power as it is assumed that charging power is kept constant during each time period. The charging power is restricted by the grid connection.

5 Case studies

Case studies are employed to determine the effectiveness of the proposed DT concept for the alleviation of distribution grid congestion from EV charging. A Danish 0.4kV distribution grid has been used to implement case studies comparing the situation with and without the application of DTs. The optimal charging behavior of a single cohort of EVs is modeled with respect to a variety of day-ahead price profiles to investigate the resulting congestion and the effectiveness of the DTs under various circumstances.

The case studies have been implemented using DigSILENT's PowerFactory and Mathworks' Matlab. The selected distribution grid is modeled in PowerFactory and the OPF function of PowerFactory is used to calculate the LMPs on the network. Day-ahead prices from Nord Pool EISpot are used to represent the predicted price of electricity. The optimal EV charging management with and without DTs is determined using the linear programming function in MATLAB.

5.1 Case Study Inputs

Distribution Grid

The distribution grid used in all case studies is shown in Figure 3. It is comprised of two 10/0.4 kV transformers, 33 cables, 33 buses and 72 household customers. One generator is located on the MV side of the 10/0.4kV transformer at the top of figure 3 to represent the supply of power to the distribution grid. The marginal cost of power from this generator is given as a time series of day-ahead prices from Nord Pool EISpot; this facilitates the calculation of LMPs at each bus. Another generator is located on the lower right-hand corner of **Figure 3**; this is used to provide reverse power to alleviate congestion, it also contributes to the calculation of the LMP.

The case studies that follow resulted in distribution level congestion on the feeders highlighted in red in **Figure 3**. This manifested itself in the form of high transformer and line loading levels.

EV data

A non-homogenous EV fleet was assumed for the EV charging management studies. The EV battery size varied according to individual EV driving requirements. It is assumed that the maximum charging power is 2.3kW (based on a 10A, 230V connection). A typical value of 150

Wh/km is used to calculate the energy consumption while driving [2]. The minimum and maximum EV battery SOC_s are set as 20% and 85%, respectively. The initial EV SOC varies by vehicle, and is set such that individual charging and driving requirements can be met; this is in accordance with the non-homogenous nature of the vehicle cohort. The initial SOC is assumed for the purposes of the case study; in reality the FOs would operate on the basis of continual optimization periods and the initial SOC would be determined from the final SOC of the previous optimization period. A summary of the EV data is listed in Table 1.

Driving data

In addition to the EV battery and charging power data, the EV driving pattern data are also very important. Driving data was provided from the Danish National Travel Survey [2]. This data is highly detailed and provides significant insight into the driving habits of Danish residents. For this study, the relevant data were as follows: driving stop and start times, distance driven during driving periods, and day of week of survey data collection. A cohort of 60 EVs was selected arbitrarily from the travel survey, with the only requirement being that the driving requirements could be met by an EV with battery capacity not exceeding 25 kWh. The EV availability for charging is defined as the periods during which the EV is at the home location. As this study is primarily concerned with congestion management on the distribution network this is an acceptable assumption; other charging behavior, such as on-street charging, will require alternative management, more likely on the real-time scale.

A realistic driving profile has been obtained by selecting vehicles from the same day; in this case a Monday has been selected. The availability of cohort for charging is illustrated in Figure 4. Each horizontal section represents a single EV, with the brown colour signifying availability to charge (at residence), and blue signifying that the EV is away from home, and therefore is unavailable to charge.

Time resolution for dynamic tariffs and EV charging management

A time resolution of 15 minutes was selected as it provides increased resolution from the traditional hourly dispatch. This allows for the high-resolution nature of EV driving behavior without requiring excessive computational power or time. Tariffs are therefore also set at 15-minute resolution, however the day-ahead market remains at hourly resolution. This is

acceptable, as the Nord Pool day-ahead market bids are placed in terms of volume [MWh/h]. Therefore, the bidding system does not require alteration for this concept.

Price Profiles

The optimal EV charging profile is dependent on the price profile; thus for a given cohort of vehicles on the test network, the level of congestion exhibited will also vary by price profile. For this reason, a number of price profiles have been simulated to explore the capabilities of the proposed LMP based DT for the prevention of congestion. The details of the simulated price profiles are supplied in Table 2. All case studies are conducted on a single cohort of EVs.

The LMP calculation is dependent on the definition of congestion; typically this is given as system component loading exceeding 100%. However, for this application this definition rarely results in complete congestion alleviation; high levels of system loading usually occur over extended periods, of which only a proportion will have system loading exceeding 100%. For this reason, a system loading limit (congestion definition for the purpose of LMP calculation) below 100% is often beneficial, as the resulting DTs will be over such a time extent as to prevent the formation of secondary congestion peaks following the application of DTs. However, if the system loading limit is too low, the resulting tariffs will be excessive and economically inefficient. For this reason, each of the price profiles examined in the case studies that follow have been tested at a range of system loading limits from 50% to 100% in increments of 10%. The most successful results are presented, and conclusions can then be drawn on the critical factors that determine the appropriate system loading level definition.

5.2 Case study results

Four case studies have carried out in order to illustrate the efficacy of the proposed day-ahead tariffs for alleviating congestion from EVs and show the needs of having a dynamic system loading limit to determine the efficient day-ahead tariffs.

In the four case studies, the EV number and the driving pattern are same. The four different price profiles specified in Table 2 have been used to implement the case studies.

The case study results are presented in figures 5-8 below. In each case the system loading curves before and after the application of DTs are presented. Day-ahead prevention of

congestion is achieved in all cases, though at different system loading limits. Most notably, congestion corresponding to a system loading of 155% is successfully prevented in both case 3 and 4. System loading of 130% is prevented in case 1.

It can be observed from case 2 that sharp peaks in system congestion do not require the application of DTs over an extended period as the adjacent system loading is sufficiently low that even with the shifting of charging, secondary congestion peaks do not occur.

In cases where the price profile exhibits frequent fluctuations, such as in cases 3 and 4, a system loading limit of 90% is sufficient to prevent congestion, as there are multiple low cost hours to which EV charging can be shifted according to the diversity in availability to charge.

However, a lower system loading limit is required in cases where price dips occur during peak charging periods such as the early evening, when EVs become available to charge after returning home. This is evident from case 1 where a system loading limit of 80% is required to fully prevent congestion.

The case study results illustrate the requirement for a dynamic system-loading limit. Setting a low limit can lead to excessive cost burdens as tariffs are applied where they are not necessary. This is also economically inefficient. Setting too high a limit can prevent the effective dispersal of charging, resulting in failure to completely alleviate congestion.

6 Conclusions

The study illustrates the efficacy of an economically efficient day-ahead DT concept for the prevention of distribution grid congestion from EVs, which can be implemented in the current Nordic market setup. The concept is found to be successful in a number of situations. It is also found that the system loading limit is a determining factor for successful prevention of distribution level congestion from EVs. The case studies have highlighted that the predicted price profile is a determining factor for the appropriate system loading limit that results in DTs that are both economically efficient and technically successful.

Further work is required to develop the concept for its application in a broader setting. Additional investigation will be required to verify the results taking into account the uncertainty of

predictions. Preliminary analysis suggests that uncertainty will increase diversity of demand, thereby reducing congestion and improving the efficacy of the DTs.

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Figure 1 Flowchart of distribution grid congestion alleviation from electric vehicles using DTs

Figure 2 Concept of distribution grid congestion alleviation from electric vehicles using DTs

Figure 3 Distribution grid from the Island of Bornholm for case studies

Figure 4 EV charging availability for Monday

Figure 5 Case Study 1 with Night-time Peak Price Profile

Figure 6 Case Study 2 with Evening Peak Price Profile

Figure 7 Case Study 3 with Sinusoidal Variation Price Profile

Figure 8 Case Study 4 with Higher Frequency Sinusoidal Variation Price Profile

Table 1

EV data summary for EV charging management study

EV Parameter	EV Parameter Value
EV battery size	25 kWh
Charging power	230 W
Energy consumption from driving	150 Wh/km
Minimum SOC	20%
Maximum SOC	85%

Table 2

Price Profile Details

Price Profile	Characteristics
1	Night-time Peak
2	Evening Peak
3	Sinusoidal Variations
4	Higher Frequency Sinusoidal Variations

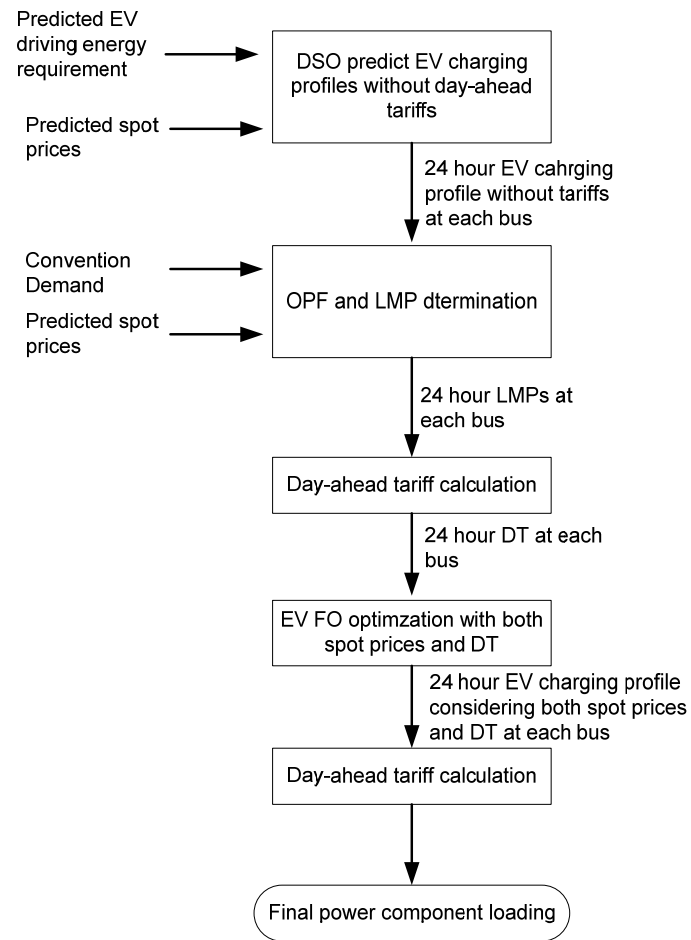


Figure 1

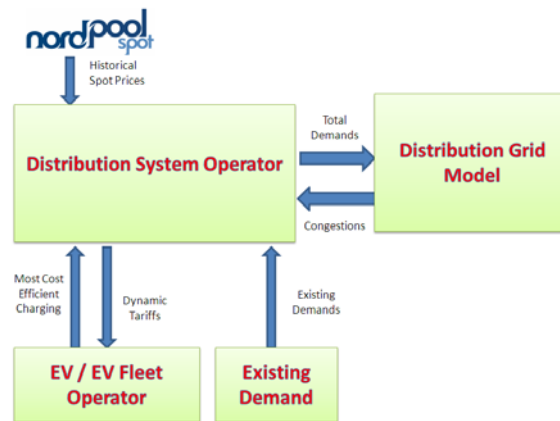


Figure 2

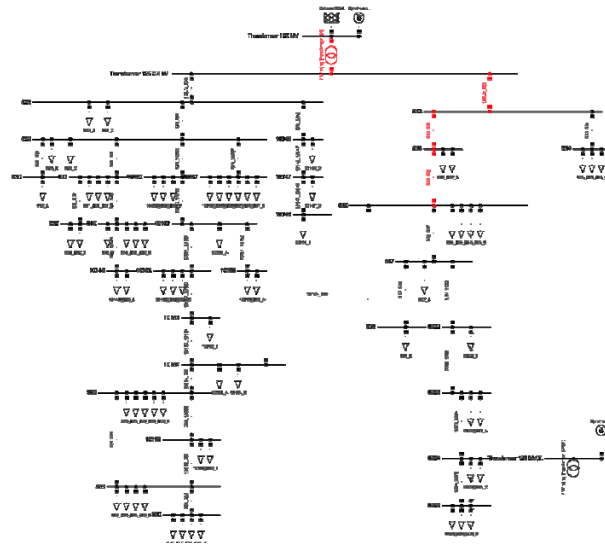


Figure 3

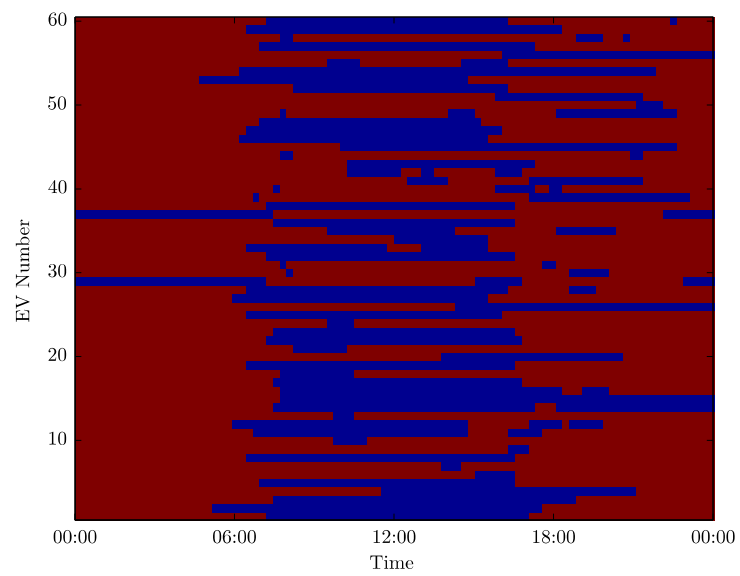


Figure 4

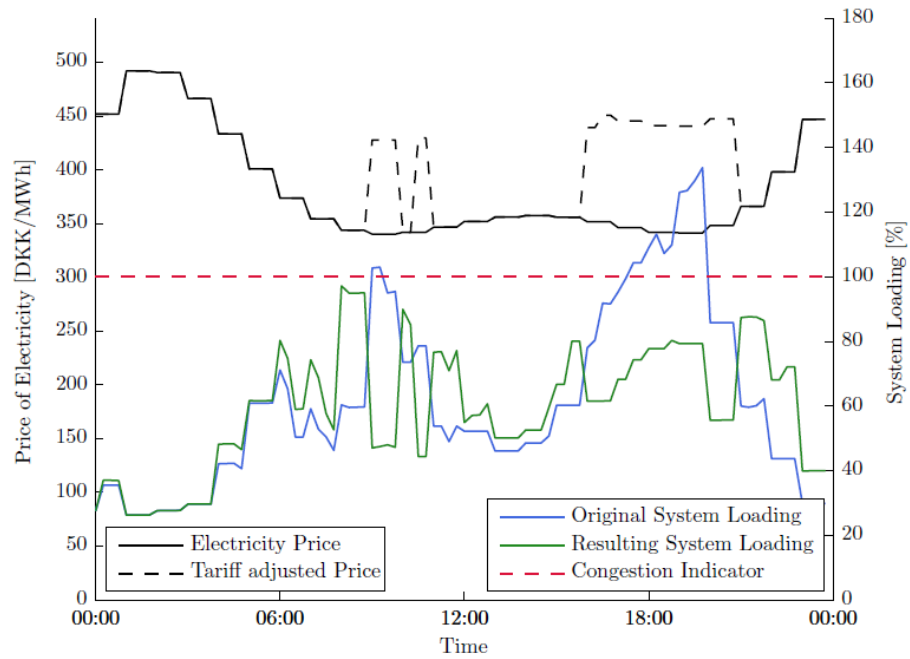


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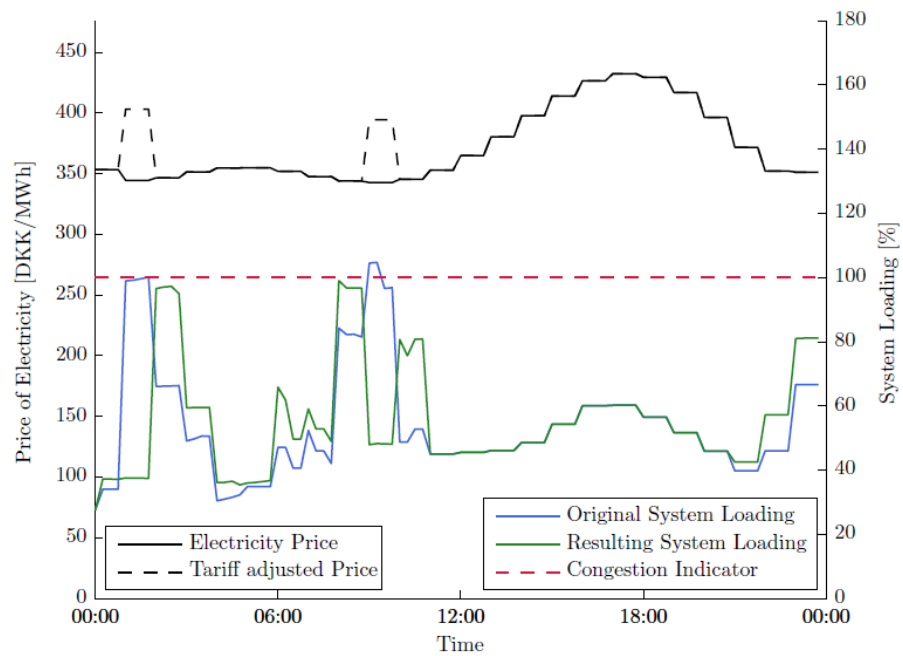


Figure 6

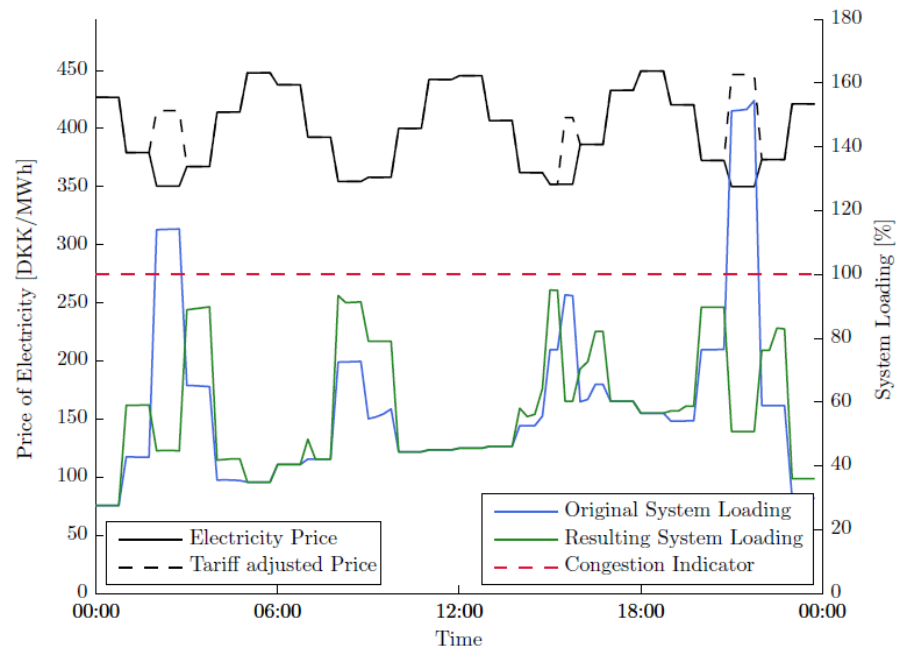


Figure 7

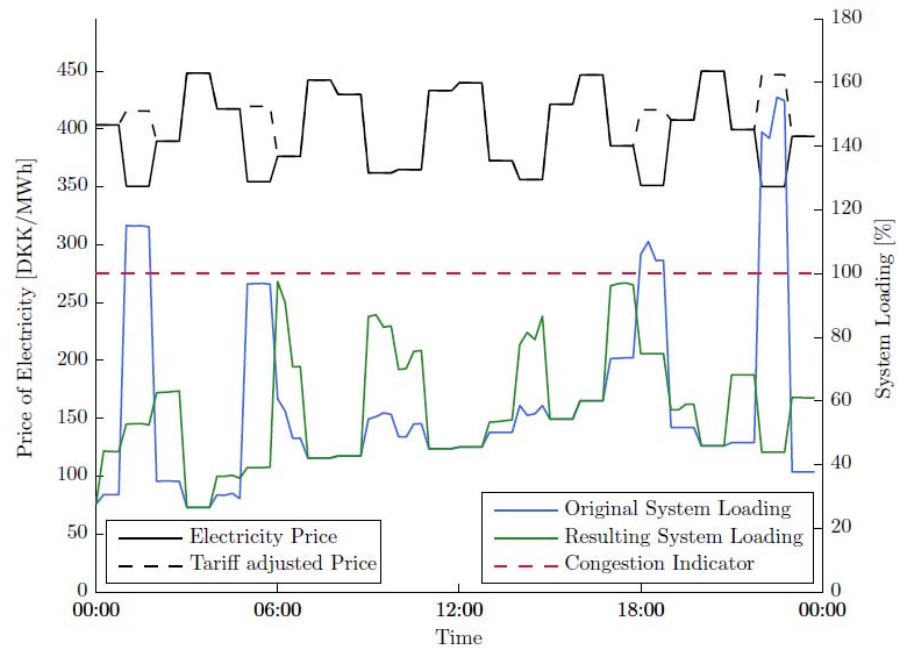


Figure 8